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Barriers in Management Research Productivity: A TISM and Fuzzy MICMAC Study

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Abstract
Despite its crucial role in the social and economic development of a nation, the output of management research in India remains limited. India significantly lags global standards for academic research output. Despite having research interests, most academics are unable to produce high-quality output. This study aims to pinpoint the barriers affecting the research output of Indian management academicians. This study identified and validated 15 barriers to research productivity among Indian management academicians through a literature review and expert discussion. Contextual linkages among barriers were drawn using the total interpretative structural modelling (TISM) technique, and a hierarchical, nine-level model was developed. Further, the driving and dependence powers of the barriers were determined through a Fuzzy MICMAC analysis. The results indicate that institutional and resource-based challenges, such as rigid grant procedures, inadequate incentives, weak research culture, and limited collaboration, act as strong driving barriers. Motivation-related constraints and workload pressures emerge as dependent barriers, influenced by deeper systemic issues.

Keywords- Management research productivity, Barriers, India, TISM, Fuzzy MICMAC.

1. Introduction

Research productivity has emerged as a defining benchmark of academic excellence in higher education institutions worldwide. Scholarly output produced by academic institutions plays a dual role: it builds institutional prestige in global and national rankings while also strengthening teaching quality, industry engagement, and policy credibility (Adams et al., 2005; Sahoo et al., 2017). Despite this fact, the concentration of high-quality academicians and researchers is trivial in the country, as most of the HEIs remain teaching-centered with minimal involvement in research activities.

To integrate education with research and develop a research climate in academia, the government of India launched several initiatives to boost research and collaboration in higher education institutions on both domestic and international scales. The National Higher Education Mission is working towards the creation of quality academic researchers in the country under the 'Institutes of Eminence (IoE)' scheme, where, 20 institutions are being transformed into world-class teaching and research institutions (University Grants

Commission, 2015). Meanwhile, the National Institutional Ranking Framework (NIRF), introduced in 2015, aims to motivate institutional research endeavours with 30% weightage for research and professional practice indicators (Ministry of Education, 2015).

Recent studies continue to show that institutional conditions strongly shape academics' research performance. Recent studies reveal that research activity is primarily constrained by the absence of research grants and infrastructure, due to inefficient administrative structures, weak governance systems, and a lack of networking, resulting in limited research collaboration and recognition (Kadikilo et al., 2024; Pascua, 2025). Meanwhile, individual motivation tends to have a weaker impact on research performance than institutional factors. Evidence from India also reflects similar outcomes. A recent study by Das (2024) highlights how the organizational climate of higher education institutions influences faculty output, while Jadhav et al. (2024) present fresh bibliometric trends from publicly funded social science institutions, pointing to persistent structural challenges that constrain research performance.

Research productivity varies across disciplines pertaining to distinct publication cultures and evaluation practices: sciences generally operate in cumulative, collaborative frameworks, whereas social sciences and humanities tend to be more individualistic and fragmented in their production and assessment of work (Wanner et al., 1981; Albert et al., 2016).

The field of management occupies a central position within this spectrum. It is required to provide robust theory and practical guidance for organisations and policymakers concurrently. The dual mission creates tensions regarding rigour and relevance, journal incentives, ranking pressures, accreditation, and practical expectations (Bennis & O'Toole, 2005; Banks et al., 2016). While business schools are expected to contribute to both theoretical and applied knowledge (Bartunek et al., 2006; Amara et al., 2016), they often face barriers that inhibit sustained research engagement.

Collectively, these factors render management research particularly vulnerable to challenges that diminish time, capacity, and motivation. A barrier-focused study is beneficial in this context. Identifying foundational constraints, their consequences, and their interrelations allows leaders to focus on a limited number of leverage points to effectively transform the research system.

Therefore, this study aims to advance the research productivity literature in management academia by developing a theory-driven causal framework that explains how barriers reinforce one another. Prior evidence is primarily descriptive and does not indicate potential areas for systemic policy change (Ab Rahman et al., 2022; Kadikilo et al., 2024). Prior studies have utilised MCDM techniques such as AHP, fuzzy AHP, or traditional ISM and MICMAC to prioritise determinants of research productivity (Raco et al., 2020; Hue et al., 2022; Ocampo et al., 2022). However, these approaches fail to capture the directionality, hierarchical level and interdependencies among the elements under study. The present analysis focuses on Indian business schools; however, the key barriers revealed under this study, such as funding and resource limitations, weak research culture, and bureaucratic rigidity, etc., are very much prevalent across management institutions in emerging economies (Das, 2024; Jadhav et al., 2024). By combining TISM with fuzzy MICMAC methodologies, this paper transcends earlier MCDM works in management research productivity. A hierarchical causal model is developed using TISM and FMICMAC, further ensuring the stability of driving-dependence relationships under uncertainty, offering stronger methodological and policy relevance for designing targeted interventions.

This paper identifies key research productivity barriers faced by management academics, and establishes as well as interprets the interrelationships among these barriers through TISM, an advanced version of traditional interpretive structural modelling (ISM) (Warfield, 1976). In addition to explaining the nature and relationships between variables, as in ISM, it also offers the reasons and rationale for these relationships. To further comprehend their relevance, the variables are grouped based on their driving strength and dependence using a fuzzy MICMAC.

The paper is structured as follows: Firstly, a review of literature on research productivity in Indian management academia identifies the existing barriers for management academicians. Then, TISM and Fuzzy MICMAC methodologies are explained, followed by their application on research productivity barriers faced by management academicians in the Indian context. Towards the end, the paper discusses the results, management implications, and recommendations for further research.

Though the paper reflects the Indian management scenario, it draws from the challenges common to the global management academia and thus provides a more nuanced understanding of how different barriers interact, offering insights for policymakers, administrators, and faculty aiming to strengthen research ecosystems in Indian management institutions.

2. Review of Literature

2.1. Research Productivity in Higher Education

Research productivity in academia is conceptualised through multiple lenses. Primarily, publication and citation counts are utilised to measure research productivity, whereas comprehensive views consider the impact and societal relevance of any research as its true yardstick (Abbott & Doucouliagos, 2004; Bartunek et al., 2006; Bentley, 2015; Amara et al., 2019). The literature reveals no single universal definition of research productivity. Instead, its meaning varies depending on whether emphasis is placed on publication quantity, citation-based influence, innovation and rigour, or alignment with institutional missions. **Table 1** synthesises widely cited conceptualisations to clarify how research productivity has been understood across studies.

Table 1. Research productivity definitions.

Authors	How they defined research productivity
Abramo & D'Angelo (2014)	Research output per researcher, often measured through a combination of publication volume and normalized citation impact (e.g., Fractional Scientific Strength).
Carpenter et al. (2014)	A combination of scholarly publication metrics, citation counts, journal prestige, and author-level impact indicators, such as the h-index.
Lindner et al. (2018)	Along with publication quantity, research productivity is also reflected through research novelty, scientific rigor, and knowledge advancement.
Teodorescu (2000)	Research productivity is measured through consistent scholarly output of a researcher, which is often influenced by institutional support, training, and academic networks.

Here, Teodorescu (2000) is a foundational source often cited in higher education research.

Although the definitions summarised in **Table 1** differ in emphasis, they converge on an important insight: research productivity is not a unidimensional construct driven solely by individual effort. Output-oriented definitions focus on publications and citations (Abramo & D'Angelo, 2014; Carpenter et al., 2014), while broader conceptualisations incorporate rigour, novelty, and knowledge advancement (Lindner et al., 2018). Teodorescu (2000) further extends this view by explicitly linking research output to institutional support structures and academic networks.

This diversity reveals a key tension in the literature. While some studies implicitly treat productivity as an individual performance outcome, others position it as an emergent result of interacting individual, organisational, and systemic conditions. Consequently, barriers to research productivity cannot be meaningfully examined in isolation. Rather, they are embedded within a multilevel ecosystem where motivational, skill-based, institutional, and policy-level constraints often reinforce one another. This insight motivates the present study’s focus on identifying not only discrete barriers but also their structural interrelationships within management academia.

Global higher education literature agrees that research productivity is crucial for academic career building and progression (Williamson & Cable, 2003; Valle & Schultz, 2011). Moreover, the reputation and competitiveness of institutions are also assessed through global rankings resulting from their research production and quality (Prathap, 2014; World University Rankings, 2020). In management academia, this conversation often calls for connecting theory with practice and making findings relevant for organisations and policy (Starkey & Madan, 2001; Lee & Greenley, 2010).

2.2 Research Productivity in Indian Academia

Many studies have looked at research productivity in Indian higher education. Early research mostly mapped publication output and trends. Some studies highlight productivity in top institutions like the IITs and leading business schools, as well as in fields such as agriculture and applied sciences (Arif, 2015; Paul et al., 2017; Sahoo et al., 2017). These works show that research output has grown over time, but the increase is not even across all institutions and disciplines.

Later studies looked beyond just counting research output and examined the conditions that shape academic research in India. Researchers have identified ongoing cultural and systemic barriers that make it difficult to maintain research activity. These barriers include a focus on teaching, few chances to develop research skills, and a weak link between research efforts and rewards (Banerjee, 2013; Singh, 2014). More recent work shows that the growing focus on rankings and performance indicators has changed what institutions and faculty prioritise. These systems have encouraged more publishing but have also increased pressure on academics, often without improving real research capacity (Marisha et al., 2017; Solanki et al., 2019). Overall, the literature suggests that while research output has gone up, deeper problems remain.

The Indian higher education system deserves close study because its institutional and regulatory structures shape research behaviour. India has rapidly expanded higher education and has a wide range of institutions. However, national assessment systems set similar research expectations for all institutions, regardless of their differences. Frameworks like the National Institutional Ranking Framework focus on publication and citation indicators, often from international databases. This means that institutions with different resources, doctoral programs, and workloads are judged by the same standards. In this context, challenges related to workload, skills, incentives, and collaboration often reinforce each other.

Academic career rules and regulations also shape this environment. In India, hiring and promotion often depend on set performance criteria that value research output (University Grants Commission, 2018). These rules encourage faculty to publish, fostering a publish-or-perish culture. Worries about journal quality and recognition also affect how faculty make research and publication choices (Jayaraman, 2018). Earlier studies show that these signals influence motivation, risk-taking, and views on research legitimacy, especially in places with limited research support.

Management academia faces its own challenges within this broader setting. Faculty in management schools often have heavy teaching loads and are expected to publish in ranked journals. The field's practical focus and the need for commercial relevance make research even harder. Many institutions also offer limited doctoral programs and weak mentoring, which further complicates matters. As a result, issues such as heavy workloads, a weak research culture, limited incentives, skill gaps, and limited collaboration are part of daily academic life. Publish-or-perish expectations intensify these pressures, adding both psychological and professional stress for management faculty (Publish or Perish, 2011; Harzing, 2016).

In summary, the barriers to research productivity in Indian management academia do not exist in isolation. They interact and strengthen each other. To understand these connections, we need more than just a list of problems. We need a framework that shows how these barriers are linked and influence each other. That is why this study uses a country-specific TISM–Fuzzy MICMAC approach to explore the structure of research productivity barriers in Indian management academia.

2.3 Research Productivity Barriers

Prior research on research productivity barriers largely follows a cataloguing approach, identifying constraints at individual, institutional, and system levels (Bland et al., 2005; Nguyen et al., 2016; Gonzalez et al., 2019). However, these studies seldom examine how such barriers interact or compound one another. For example, a weak research culture may exacerbate motivational decline, while heavy teaching workloads can limit skill development and collaboration opportunities. As a result, existing literature provides limited guidance on which barriers act as root causes and which emerge as downstream consequences. Addressing this gap requires a framework capable of capturing both the presence and the interdependence of barriers, which informs the analytical approach adopted in this study.

Various barriers affect the research quality and productivity of academics at individual, institutional, industry and policy levels. These are discussed as follows:
1) *No research motivation post-promotion*: Extrinsic rewards are not as prominent after the promotion and tenure of a faculty. For this reason, faculty members are less driven to conduct research as rigorously as they did to gain promotions (Chen et al., 2006). Intrinsic rewards are the only motivation source after the promotion and are hardly sought by the faculty in general, especially in teaching-oriented organisations (Hardre et al., 2011). Also, faculty members welcome financial rewards more than spiritual ones (Hu & Gill, 2000). After promotion, faculty members may be less inclined towards undertaking new research.

2) *Lack of professional development*: Fewer initiatives and efforts to improve subject knowledge and research skills through workshops, education courses, and colleagues gathering to share expertise. Also, the teaching-oriented leadership/nature of the institute operates as a barrier in the promotion of research culture (Bland et al., 2005; Gonzalez et al., 2019).

3) *Weak research and language skills*: Researchers have insufficient knowledge of basic/ advanced skills to conduct and write research. Faculty may have good research ideas, essential to publish in top-rated journals, but are unable to execute them due to a lack of expertise. Also, faculty members lack the required technical language/ communication skills to be applied in the field of management research. Papers not written in quality English lead to straight rejections by editors. Additionally, weak language can affect networking adversely (Balakrishnan, 2013; Wieczorek & Mitręga, 2014).

4) *Heavy family commitments*: Time-consuming family responsibilities such as marriage, household duties, dependent childcare, or ageing parents leave less time to devote to research and writing for the faculty. Sometimes, the problem is severe enough to force faculty (especially females) to leave academe or choose non-tenure-track positions, which leads to less research involvement, thereby threatening the overall productivity of the faculty (Aiston & Jung, 2015; Guraya et al., 2018).

5) *No research incentives and rewards*: Non-existence of a reward structure/policy for research achievement in the organisation. Monetary rewards such as salary increments based on research performance are potential extrinsic rewards that act as a strong motivational driver to a faculty member. (Chen et al., 2006; Nguyen et al., 2016)

6) ***Lack of resources*****:** Lack of funding support for faculty to travel to and attend professional and research-based conferences, which help faculty to explore new research avenues, networking, and research updates (Bland et al., 2005). Also, the unavailability of research support staff is required due to their multiple teacher, advisor, or mentor roles. Management research requires access to research facilities too, such as research labs, library resources (offline/online), online databases, and journals from various publication houses (Balakrishnan, 2013). Outdated research facilities due to heavy subscription fees and financial constraints of the institution. Also, a few graduate students possess research interests and aptitude to boost additional intellectual resources for faculty's research work (Snowball & Shackleton, 2018).

7) ***Teaching and service workload*****:** Overload of courses taught, mentoring, advising, and remediating students leaves less time to pursue research (Hardre et al., 2011; Jung, 2012). Administrative and leadership duties, along with teaching, research, and engagement with academic committees, are like wearing too many hats. Moreover, if an institute is teaching-centric, the research output of faculty may not ensure job security (Smolentseva, 2011; Nguyen et al., 2016).

8) ***Tight research grant criteria*****:** The criteria followed by funding agencies are strict and inflexible and it's impossible for the faculty to always meet them. Moreover, due to demand and supply, these rules keep on changing. Close monitoring and frequent deadlines also demotivate faculty to undertake grant-based research (Khalil & Khalil, 2019). Faculty members find it difficult to attract funding from outside sources for research since either the faculty is unable to write good proposals or it is highly competitive to get funding due to a large number of applicants. Faculty with research publications have a higher chance of winning grants than others. Also, no awareness of funding sources and limited collaborators in the institution. (Okiki, 2013; Guraya et al., 2018).

9) ***No industry support*****:** Faculty benefit from industry collaborations in terms of interactive learning, motivation for novel research through the generation of new ideas owing to the knowledge shared by the industry, and access to monetary and non-monetary resources (Balakrishnan, 2013; Garcia et al., 2019). Also, joint research projects with industrial partners are more likely to result in good publications. Lack of support of such calibre can be a disadvantage for the faculty.

10) ***Absence of recognition*****:** Recognition and acknowledgement for the research achievements are a source of intrinsic motivation for a faculty (Chen et al., 2006). Intrinsic rewards have a positive bearing on the research output. Also, recognition of research work by peers helps to develop a research culture in the organisation (Memarpour et al., 2015).

11) ***Low stakeholder relevance of research*****:** Contribution to society is an intrinsic motivator for a researcher (Bland et al., 2005). Some faculty won't be interested and enthusiastic about a research project without an altruistic motivation (Hedjazi & Behravan, 2011; Albert et al., 2016).

12) ***Top-journal rejection phobia*****:** Past experiences of rejection can develop a feeling of disappointment, fear, and doubt in one's work. Publishing in top journals requires a clear contribution, and it's very demanding. Acceptance rates are very low (close to 2% in some cases) as journals receive thousands of manuscripts and only a few are accepted. Rejections may demotivate the faculty to undertake further research. At the same time, publishing in top journals brings professional and personal value.

13) ***No intrinsic research motivation*****:** Faculty lack the drive to initiate new projects or the required discipline to continue with the existing ones. Faculty may get demotivated due to the absence of tangible and intangible rewards, lack of a commonly held vision of the faculty and the institute, and low confidence in the direction of research work (Hardre et al., 2011; Yarris et al., 2014).

14) ***Weak research culture*****:** Lack of appreciation from peers for the research work done, nonexistence of a collegial atmosphere for research and recognition from peers due to lack of socialisation of the faculty staff into a research climate. For example, faculty do not produce peer-reviewed articles due to a lack of local recognition of the research study. No culture of group participation or a sense of community to conduct research work exists in the institution. They lack the motivation to test novel concepts and do not share beliefs and behaviours connected to research (Hoffmann et al., 2014; Gonzalez et al., 2019). Peers, mentors, and seniors frequently suggest opportunities that will increase funding and give faculty members more opportunities to publish through co-authorship and collaboration. Having mentors who can critique and edit their work and offer insightful comments on research concepts is also beneficial to the researcher. Lack of mentorship slows down the research process, or, in case of difficulty, faculty might just quit the process (Ibegbulam & Jacintha, 2016; Allen et al., 2018). Eminent personalities exist in very few organisations for a researcher to look up to, especially during the initial stages of their research career. Faculty members learn the abilities and information required for a prosperous research career in their discipline by emulating such individuals. The absence of such role models deprives a faculty of the motivation to develop and pursue achievement-oriented goals (Conn et al., 2005).

15) ***Weak networking and collaboration*****:** Resistance among faculties towards working in collaboration with others due to personal, social, or environmental factors. Some faculty work more effectively alone because they lack the skills necessary to work in collaboration, and it becomes a time-consuming task for them to adjust to others. Such faculty do not derive benefit from joint research and prefer to work in isolation. (White et al., 2012; Nguyen et al., 2016). Limited opportunities are available to establish networks with potential co-researchers within or outside the organisation. Faculty lack guidance and help in terms of research training, accessibility to statistical design, study design or writing expertise, or assembling a skilled research team. Few people have enough knowledge of statistical analysis, and people who know well do not want to assist (Yarris et al., 2014). Thus, accessing research expertise gets tough, universities take up fewer joint research projects, and few prospects are available to create new research ideas and funds.

Table 2. Barriers to management research productivity.

Barrier code	**Research productivity barrier**	**Primary conceptual focus**	**Identified studies**
B1	No research motivation post-promotion	Career-stage–specific motivational decline following attainment of promotion or tenure	Hu & Gill (2000), Chen et al. (2006), Hardre et al. (2011)
B2	Lack of professional development	Skill enhancement and continuous research capability development	Hardré et al. (2007), Hardré (2012), Lodhi (2012), Gonzalez et al. (2019)
B3	Weak research and language skills	Individual-level technical and academic communication competence	Bland et al. (2005), Balakrishnan (2013), Wieczorek & Mitręga (2014)
B4	Heavy family commitments	Personal and family-related time constraints affecting research engagement	Aiston & Jung (2015), Guraya et al. (2018), Snowball & Shackleton (2018)
B5	No research incentives and rewards	Organizational-level extrinsic reward and incentive structures	Fairweather & Rhoads (1995), Chen et al. (2006), Nguyen et al. (2016)
B6	Lack of resources	Institutional availability of financial, infrastructural, and research support resources	Bland et al. (2005), Smolentseva (2011), Okiki (2013), Snowball & Shackleton (2018)
B7	Teaching and service workload	Allocation of academic time across teaching, service, and administrative roles	Chen et al. (2006), Jung (2012), Lodhi (2012), Nguyen et al. (2016)
B8	Tight research grant criteria	Policy- and funding-agency–driven constraints on research initiation	Hardre et al. (2011), Okiki (2013), Guraya et al. (2018)

Table 2 continued…

B9	No industry support	External stakeholder engagement and industry–academia linkage	Balakrishnan (2013), Mahajan et al. (2016), Garcia et al. (2019)
B10	Absence of recognition	Organizational and peer-level acknowledgment of research contributions	Chen et al. (2006); Memarpour et al. (2015)
B11	Low stakeholder relevance of research	Perceived societal and practitioner relevance of research outcomes	Bland et al. (2005), Hedjazi & Behravan (2011), Albert et al. (2016)
B12	Top-journal rejection phobia	Psychological and experiential barriers related to perceived publication risk	Recommended by group of experts
B13	No intrinsic research motivation	Individual-level intrinsic drive toward research activity	Ryan and Deci (2000), Hardre et al. (2011), Yarris et al. (2014)
B14	Weak research culture	Institutional norms, values, and shared expectations supporting research	Hoffmann et al. (2014), Mahajan et al. (2016), Gonzalez et al. (2019)
B15	Weak collaboration and networking	Relational and behavioral aspects of joint research and scholarly interaction	Conn et al. (2005), White et al. (2012), Nguyen et al. (2016), Allen et al. (2018)

Global management research is impeded by the numerous barriers identified in the existing literature; however, none have identified the strength and mutual influence of these barriers on one another, thereby identifying key barriers driving other issues. **Table 2** presents the summary of key research productivity barriers in management academia identified in this study. To ensure that the identified barriers are not only contextually relevant but also conceptually grounded, the following section outlines the theoretical foundations that inform the causal structure developed in this study.

2.4 Theoretical Foundations of the Barrier Framework

The structural relationships among the identified barriers are grounded primarily in institutional theory, which explains how governance structures, norms, and policy environments shape academic behaviour and performance in higher education settings (Scott, 2008). This theoretical lens aligns closely with the model's findings, where bureaucratic procedures, rigid grant regulations, limited autonomy, and weak research-supporting culture operate as strong driving forces that condition how faculty access and utilise resources, collaborate, and engage in research. These institutional constraints serve as mediators for the systemic barriers that ultimately influence research productivity.

Similarly, the resource-based view (RBV) highlights the role of monetary and non-monetary resources, such as funding, digital infrastructure, and administrative support, in institutions' research output (Barney, 1991).

Further, the social capital theory suggests that collaboration networks, mentorship, and research communities are essential enablers of knowledge sharing and motivational reinforcement (Nahapiet & Ghoshal, 1998). The mid-level positioning of these barriers in the TISM model reflects their dependence on institutional factors while shaping individual research performance.

Perspectives rooted in theories of motivation, particularly self-determination theory, explain how individual-level constraints, such as rejection anxiety, low intrinsic motivation, or insufficient recognition, can become dependent barriers when individual autonomy, competence, and relatedness are neglected (Deci & Ryan, 2000).

Collectively, these theoretical views strengthen the interpretive logic in the TISM hierarchy. The institutional environment and support are the primary drivers of productivity, while resources, motivation, and social contexts serve as transmission pathways. Hence, the barrier framework under study is theoretically grounded rather than solely derived from expert opinions.

2.5 Research Gap and Objectives

Although past research has documented barriers that affect academic research productivity, most studies remain descriptive, focusing on identifying and ranking factors without explaining how they interact as a system (Hesli & Lee, 2011; Ramírez-Montoya et al., 2023). A few recent studies have applied multi-criteria decision-making methods such as AHP or fuzzy AHP to prioritise determinants of lecturer research productivity (Raco et al., 2020; Hue et al., 2022; Sharma et al., 2024), but these approaches primarily assign weights to predefined criteria and still treat barriers as largely independent. They do not model the directional, hierarchical causal relationships among constraints, nor do they distinguish systematically between deep structural drivers and outcome-level symptoms. As a result, they offer limited insight into how institutional constraints, workload pressures, restricted access to funding, and motivational issues reinforce one another in management academia.

Moreover, existing research in the Indian context has not sufficiently distinguished high-leverage structural constraints from barriers that are more symptomatic or dependent, which makes it difficult for policymakers to prioritise interventions. There is also a lack of theory-driven causal models that capture how resource availability, institutional culture, and individual capabilities co-evolve to shape sustained research performance.

To address these gaps, this study makes the following contributions:

1) This study constructs a structured causal framework of research productivity barriers using Total Interpretive Structural Modelling (TISM). This method improves theoretical interpretation beyond traditional ISM by elucidating the fundamental logic of each directional relationship.
2) This study employs Fuzzy MICMAC analysis to evaluate the stability of driving-dependence relationships in the face of uncertainty, thereby providing a more precise identification of the barriers where policy intervention would yield the most significant systemic impact.
3) We are generating a context-specific model, grounded in expert knowledge from Indian management schools, which advances the predominantly generic global literature by reflecting local institutional complexities.
4) The study offers a comprehensive set of actionable strategies to mitigate the critical barriers based on their intensity and influence within the system.

3. Methodology of Research

This study aims to elucidate the primary obstacles to research productivity among Indian management academicians and to comprehend their interconnections. To systematically model these interconnected barriers, this study utilises a research methodology that combines TISM and Fuzzy MICMAC, rather than relying on traditional MCDM or purely statistical approaches. Other MCDM methods, such as AHP and TOPSIS, treat factors independently, ignoring their interdependencies among barriers. Moreover, statistical methods like Structural Equation Modelling (SEM) are purely quantitative. Also, these require large datasets and assume predefined linear relationships, which are often unavailable or fail to capture the contextual complexity inherent in institutional research settings. In contrast, TISM helps reveal a hierarchical causal structure with interpretive logic behind each link, clarifying why one barrier influences another. TISM is an advanced version of the traditional ISM model as described by Sushil (2012), which offers an enhanced framework for organising elements and understanding their interconnections. In addition to the identification of variables and their linkage as in traditional ISM (Warfield, 1974; Sage, 1977), TISM incorporates specific reasoning for each relationship and its direction to evaluate the model's validity (Sushil, 2017). It creates a hierarchical structure of the study variables through an interactive expert-driven process and provides interpretation for the rationale behind each relationship (Sindhwani et al., 2019). The digraph systematically depicts the interrelations among the factors (Hasan et al., 2019), enabling the dual function of developing a thorough interpretive structural model while also constructing a knowledge repository capturing causal logic and interdependencies.

To further improve analytical rigour due to decision-making under uncertainty, fuzzy MICMAC (Matrice d'Impacts Croisés Multiplication Appliquée) adds a score-based classification of barriers into driving, dependent, linkage, and autonomous categories. Utilising the results of the TISM hierarchy, MICMAC organises variables as per their driving strength and dependence (Qureshi et al., 2008). Watson (1978) demonstrated that MICMAC effectively prioritises critical variables by assessing their numerous indirect interconnections that often shape systemic behaviour more than direct effects (Saxena et al., 1992). Incorporating fuzzy logic enhances this analysis by relaxing binary assumptions and increasing sensitivity under ambiguous expert evaluations. This combination of methods is applied in several domains, such as supply chain and sustainable procurement studies, where the problems of barrier interdependencies and uncertain expert judgments prevail (Chandra and Kumar, 2018; Sharma et al., 2021; Hasan et al., 2024; Masudin et al., 2025). This assures that TISM with fuzzy MICMAC yields more reliable and policy-relevant hierarchical models. For instance, in sustainable procurement for SMEs, ISM with fuzzy MICMAC analysis exposed financial constraints as foundational barriers whose influence cascades through structural and regulatory dependencies. A combined TISM with fuzzy MICMAC approach is particularly suited to research productivity studies, where barriers are highly interdependent and expert judgments involve uncertainty.

Given the context-specific, qualitative, but systemic nature of barriers in Indian management academia, where quantitative data are limited, this combined methodology is particularly well-suited. It allows insights and experiences of experts to shape a theory-driven, contextually grounded framework, while offering analytical robustness through fuzzy-based classification.

4. Data Analysis

The research was performed in the following phases:

Phase 1: At first, a thorough literature review uncovered 21 common barriers. To compile a definitive list of key barriers in the Indian context, 30 academia and industry experts from NIRF (2022) ranked management institutions were consulted. Expert judgment forms a central component of interpretive structural modelling and fuzzy MICMAC analysis, and its validity depends on both expert competence and diversity. In this study, Expert selection was performed through purposive snowball sampling, a preferred method for MCDM studies where specialised domain expertise is required, and comprehensive sampling frames are unavailable (Reid, 1988; Landeta, 2006). While snowball sampling may introduce selection bias, this risk was addressed through explicit inclusion criteria and heterogeneity in expert profiles.

Experts were drawn from NIRF-ranked management institutions across different ownership types and rank bands, and included both research-active and non-research-active academics. The inclusion of both groups was a deliberate design choice rather than an incidental outcome. Research-active faculty contribute insights related to publication processes and performance expectations, while non-research-active academics are often more directly exposed to structural constraints such as heavy teaching workload, administrative responsibilities, and limited institutional research support. Prior studies caution that relying exclusively on highly productive researchers may underrepresent systemic and workload-related barriers, thereby introducing a different form of systematic bias (Smolentseva, 2011; Okiki, 2013). To mitigate the risk that perceptions from either group would dominate the results, expert judgments were aggregated using a majority-rule consensus approach. Barriers and contextual relationships were retained only when supported by multiple experts, and no single expert judgment determined the model structure. This approach is consistent with established practices in interpretive and fuzzy MCDM studies, where shared cognition across expert groups is prioritised over individual opinion (Warfield, 1974; Sushil, 2012).

The final set of each expert holds diverse experiences across varied management and industry sectors and is a recognised expert in their teaching/research/industry domains. We have provided a detailed profile of the respondents in Appendix A, including their institution ownership and NIRF rank range. A total of 15 barriers approved by the majority of experts were finalised for the current study.

Phase 2: The second phase involved establishing a contextual relationship among the barriers using TISM. 14 academia and industry experts agreed to participate in the TISM and FMICMAC survey. The inclusion criteria required each expert to have at least 5 years of academic experience, a PhD, and business or industry experience, particularly for non-research-active respondents. It was assured that the respondents had both contextual understanding and informed judgment about research productivity challenges in Indian management schools. An interpretive matrix was subsequently derived, wherein the relationships within the contextual matrix were analysed through the knowledge and experience of the expert academicians.

The respondents of the study are a varied mix of active and non-active researchers at different career stages. This integration is targeted to capture the comprehensive views and challenges faced by faculty across all ranges. The process of developing TISM includes the following steps (Sushil, 2012):

4.1 Barrier Identification

The barriers to higher education institution growth are identified through literature review and expert discussions, as previously presented in **Table 2.**

4.2 Establishing Contextual Relationships

The ISM methodology employs expert opinion through diverse management techniques to model and classify the barriers by establishing contextual relationships among barriers (Ahuja et al., 2009). In order to establish the contextual relationship among the final 15 barriers, 14 experts were approached for consultation. using V, A, X, and O symbols indicating the directional flow among the barriers (Faisal et al., 2019). As a result, a structural self-interaction matrix (SSIM) was generated, presented in **Table 3**.

Table 3. SSIM.

S. No.	Barrier name	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1
1.	No research motivation post-promotion	A	A	A	A	A	A	A	A	A	A	A	A	A	A	-
2.	Lack of professional development	A	A	O	O	O	V	O	O	A	A	A	A	V	-	-
3.	Weak research and language skills	A	A	X	V	O	V	O	O	O	A	O	O	-	-	-
4.	Heavy family commitments	O	O	V	O	O	O	O	O	O	O	O	-	-	-	-
5.	No research incentives and rewards	O	X	O	O	O	V	O	O	O	O	-	-	-	-	-
6.	Lack of resources	V	X	V	V	O	O	A	A	O	-	-	-	-	-	-
7.	Teaching and service workload	O	A	V	V	O	O	O	O	-	-	-	-	-	-	-
8.	Tight research grant criteria	O	V	O	O	O	O	O	-	-	-	-	-	-	-	-
9.	No industry support	X	A	V	O	A	O	-	-	-	-	-	-	-	-	-
10.	Absence of recognition	A	A	O	O	O	-	-	-	-	-	-	-	-	-	-
11.	Low stakeholder relevance of research	O	O	O	V	-	-	-	-	-	-	-	-	-	-	-
12.	Top-journal rejection phobia	A	A	O	-	-	-	-	-	-	-	-	-	-	-	-
13.	No intrinsic research motivation	A	A	-	-	-	-	-	-	-	-	-	-	-	-	-
14.	Weak research culture	V	-	-	-	-	-	-	-	-	-	-	-	-	-	-
15.	Weak collaboration and networking	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Note(s): Barrier No.: V: Variable i will help achieve variable j; A: Variable j will be achieved by variable i; X: Variables i and j will help achieve each other; and O: Variables i and j are unrelated.

4.3 Initial Reachability Matrix

In this step, the SSIM was transformed into a binary initial reachability matrix (IRM) by assigning values of 1 or 0 based on their V, A, X, and O relationships. **Table 4** presents the resultant IRM adhering to the substitution rule (Faisal et al., 2019).

Table 4. IRM.

Barrier No.	Barrier name	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1.	No research motivation post-promotion	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2.	Lack of professional development	1	1	1	0	0	0	0	0	0	1	0	0	0	0	0
3.	Weak research and language skills	1	0	1	0	0	0	0	0	0	1	0	1	1	0	0
4.	Heavy family commitments	1	1	0	1	0	0	0	0	0	0	0	1	1	0	0
5.	No research incentives and rewards	1	1	0	0	1	0	0	0	0	1	0	0	0	1	0
6.	Lack of resources	1	1	1	0	0	1	0	0	0	0	0	1	1	1	1
7.	Teaching and service workload	1	1	0	0	0	0	1	0	0	0	0	1	1	0	0
8.	Tight research grant criteria	1	0	0	0	0	1	0	1	0	0	0	0	0	1	0
9.	No industry support	1	0	0	0	0	1	0	0	1	0	0	0	1	0	1
10.	Absence of recognition	1	0	0	0	0	0	0	0	0	1	1	0	0	0	0
11.	Low stakeholder relevance of research	1	0	0	0	0	0	0	0	0	0	1	1	0	0	0
12.	Top-journal rejection phobia	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0
13.	No intrinsic research motivation	1	0	1	0	0	0	0	0	0	0	0	0	1	0	0
14.	Weak research culture	1	1	1	1	1	1	1	0	1	1	0	1	1	1	1
15.	Weak collaboration and networking	1	1	1	0	0	0	0	0	1	1	0	1	1	0	1

4.4 Final Reachability Matrix

To validate all evaluated relations, the first reachability matrix underwent a transitivity check, in which the established links were carefully examined. (Chaple et al., 2018). If barrier B_i leads to barrier B_j and barrier B_j leads to barrier B_k, then barrier B_i must lead to barrier B_k, where i, j, k = 1, 2, 3, …, 12. The process of identifying and resolving these gaps is known as a transitivity check (Kumar & Rahman, 2017). The gaps identified in **Table 4** were adjusted through the integration of transitivity relations. **Table 5** presents the final reachability matrix, where transitivity is denoted as 1*.

Table 5. FRM.

Barrier No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Driving power
1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
2	1	1	1	0	0	0	0	0	0	1	1*	1*	1*	0	0	7
3	1	0	1	0	0	0	0	0	0	1	1*	1	1	0	0	6
4	1	1	1*	1	0	0	0	0	0	1*	1*	1	1	0	0	8
5	1	1	1*	1*	1	1*	1*	0	1*	1	1*	1*	1*	1	1*	14
6	1	1	1	1*	1*	1	1*	0	1*	1*	1*	1	1	1	1	14
7	1	1	1*	0	0	0	1	0	0	1*	1*	1	1	0	0	8
8	1	1*	1*	1*	1*	1	1*	1	1*	1*	1*	1*	1*	1	1*	15
9	1	1*	1*	1*	1*	1	1*	0	1	1*	1*	1*	1	1*	1	14
10	1	0	0	0	0	0	0	0	0	1	1	1*	0	0	0	4
11	1	0	0	0	0	0	0	0	0	0	1	1	0	0	0	3
12	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	2
13	1	0	1	0	0	0	0	0	0	1*	1*	1*	1	0	0	6
14	1	1	1	1	1	1	1	0	1	1	1*	1	1	1	1	14
15	1	1	1	1*	1*	1*	1*	0	1	1	1*	1	1	1*	1	14
Dependency power	15	9	11	7	6	6	7	1	6	12	13	14	11	6	6	

Note(s): *1*entries are included to incorporate transitivity*

4.5 Level Partitioning

In TISM, the level partition process was very similar to that in ISM. To obtain the reachability and antecedent sets, all those barriers whose intersection was the same as the reachability set were stacked at the top. The barrier whose level was identified was removed from the set, and the process continued repetitively until the levels for all barriers were determined. (**Table 6**) and a final conical matrix depicting relationships and levels is produced (**Table 7**).

Table 6. Barriers level iterations.

S. No.	Barrier name	Reachability set	Antecedent set	Intersection set	Level
1.	No research motivation post-promotion	1	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15	1	I
12.	Top-journal rejection phobia	12	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15	12	II
11.	Low stakeholder relevance of research	11	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 13, 14, 15	11	III
10.	Absence of recognition	10	2, 3, 4, 5, 6, 7, 8, 9, 10, 13, 14, 15	10	IV
3.	Weak research and language skills	3, 13	2, 3, 4, 5, 6, 7, 8, 9, 13, 14, 15	3, 13	V
13.	No intrinsic research motivation	3, 13	2, 3, 4, 5, 6, 7, 8, 9, 13, 14, 15	3, 13	V
2.	Lack of professional development	2	2, 4, 5, 6, 7, 8, 9, 14, 15	2	VI
4.	Heavy family commitments	4	4, 5, 6, 8, 9, 14, 15	4	VII
7.	Teaching and service workload	7	5, 6, 7, 8, 9, 14, 15	7	VII
5.	No research incentives and rewards	5, 6, 9, 14, 15	5, 6, 8, 9, 14, 15	5, 6, 9, 14, 15	VIII
6.	Lack of resources	5, 6, 9, 14, 15	5, 6, 8, 9, 14, 15	5, 6, 9, 14, 15	VIII
9.	No industry support	5, 6, 9, 14, 15	5, 6, 8, 9, 14, 15	5, 6, 9, 14, 15	VIII
14.	Weak research culture	5, 6, 9, 14, 15	5, 6, 8, 9, 14, 15	5, 6, 9, 14, 15	VIII
15.	Weak collaboration and networking	5, 6, 9, 14, 15	5, 6, 8, 9, 14, 15	5, 6, 9, 14, 15	VIII
8.	Tight research grant criteria	8	8	8	IX

Table 7. Conical matrix.

Barrier No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Levels
B1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
B12	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2
B11	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	3
B10	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	4
B3	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	5
B13	0	0	0	1*	1	1	0	0	0	0	0	0	0	0	0	5
B2	0	0	0	0	1	1*	1	0	0	0	0	0	0	0	0	6
B4	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	7
B7	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	7
B5	0	0	0	0	0	0	0	1*	1*	1	1*	1*	1	1*	0	8
B6	0	0	0	0	0	0	0	1*	1*	1*	1	1*	1	1	0	8
B9	0	0	0	0	0	0	0	1*	1*	1*	1	1	1*	1	0	8
B14	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	8
B15	0	0	0	0	0	0	0	1*	1*	1*	1*	1	1*	1	0	8
B8	0	0	0	0	0	0	0	0	0	1*	1	1*	1	1*	1	9
Levels	1	2	3	4	5	5	6	7	7	8	8	8	8	8	9	

4.6 Development of TISM-based Digraph

To construct the TISM, the barriers were organised into levels and connected using arrows that corresponded to the conical matrix. For clarity's sake, we omitted the transitive relations. **Table 8** provides a brief interpretation of the linkages, and **Figure 1** displays the TISM model.

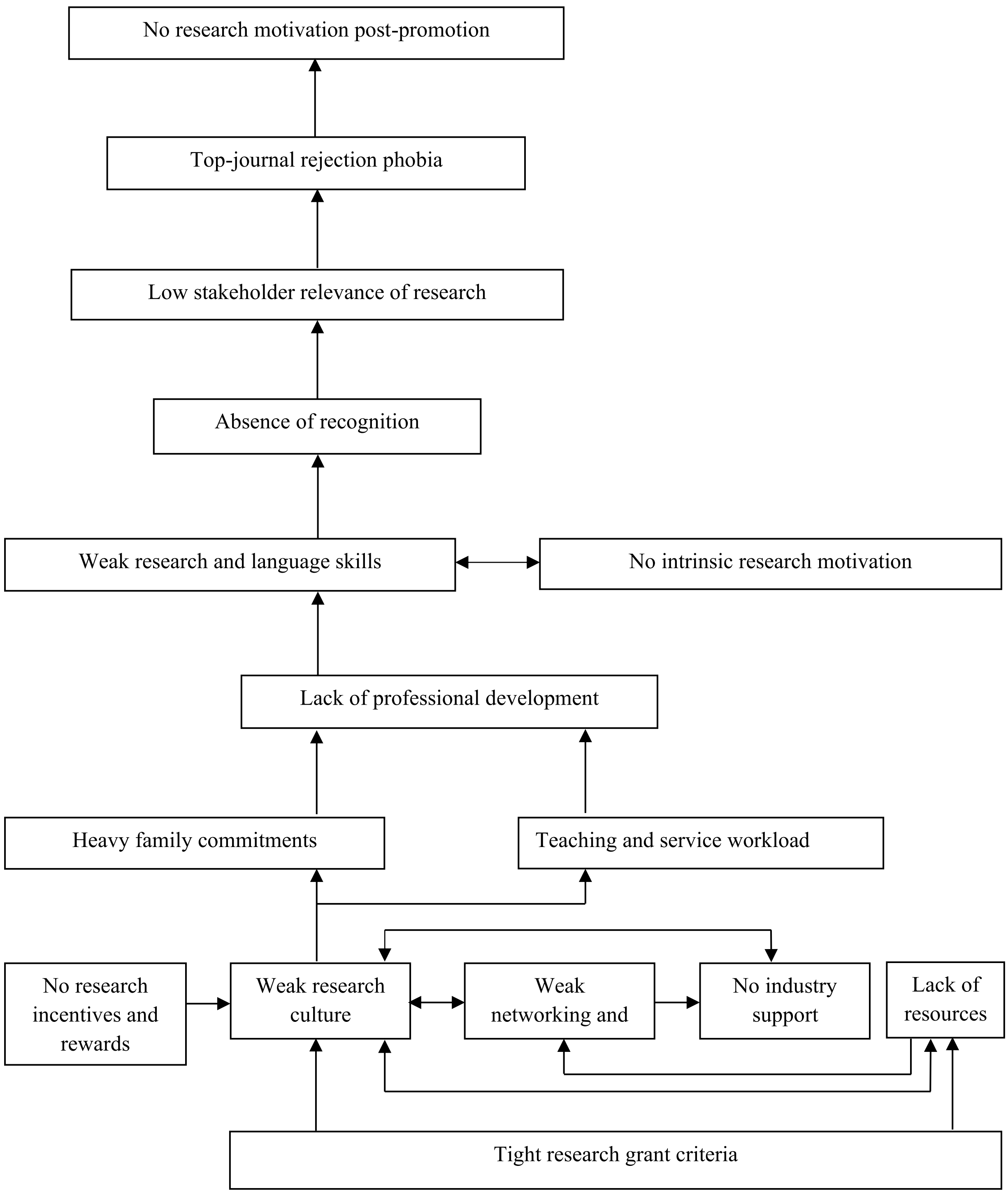

Figure 1. TISM-based model.

Table 8. Interpretive matrix for TISM of research productivity barriers.

No.	B1	B12	B11	B10	B3	B13	B2
B1	-	-	-	-	-	-	-
B12	Rejection fear further drops the research motive after promotion	-	-	-	-	-	-
B11	-	Poor stakeholder fit raises rejection risk from top journals	-	-	-	-	-
B10	-	-	Weak recognition systems dampen audit/assessment emphasis	-	-	-	-
B3	-	-	-	Weak methods/writing reduce publication quality and visibility	-	Skill gaps erode self-efficacy and research drive.	-
B13	-	-	-	-	Low research drive discourages training and feedback, limiting skills	-	-
B2	-	-	-	-	Without PD, methods and writing stay below par	-	-
B4	-	-	-	-	-	-	Familial duties limit time and mobility for PD
B7	-	-	-	-	-	-	Heavy workload crowds out time for PD activities
B5	-	-	-	-	-	-	-
B6	-	-	-	-	-	-	-
B9	-	-	-	-	-	-	-
B14	-	-	-	-	-	-	-
B15	-	-	-	-	-	-	-
B8	-	-	-	-	-	-	-
No.	B4	B7	B5	B6	B9	B14	B15
B1	-	-	-	-	-	-	-
B12	-	-	-	-	-	-	-
B11	-	-	-	-	-	-	-
B10	-	-	-	-	-	-	-
B3	-	-	-	-	-	-	-
B13	-	-	-	-	-	-	-
B2	-	-	-	-	-	-	-
B4	-	-	-	-	-	-	-
B7	-	-	-	-	-	-	-

Table 8 continued…

B5	-	-	-	-	-	No research recognition curbs research engagement	-
B6	-	-	-	-	-	Resource scarcity inhibits research	No funds for professional meets curbs ties and joint projects
B9	-	-	-	Fewer industry ties mean less data access, and co-funding	-	-	Weak industry links shrink collaboration opportunities
B14	Thin research culture lacks flexibility, worsening work-life conflict.	Non-importance of research fuels teaching-centric attitude	Weak research culture neglects recognition and rewards.	Low institute research priority cuts budgets and support.	Little outreach/liaison suppresses industry engagement.	-	Thin research climate suppresses collaboration.
B15	-	-	-	-	Limited collaboration shrinks global liaison capacity	-	-
B8	-	-	-	Tight, shifting grant rules constrain fund support	-	Strict/inflexible grant rules discourage faculty research	-

4.7 Integration of ISM and FMICMAC

The MICMAC analysis is strengthened by modelling the degree of reachability, not just whether a link exists. Because the traditional approach uses binary ties, fuzzy set theory is utilised to capture finer variations in influence. In fuzzy MICMAC, each connection carries additional information about how likely the elements are to interact. This likelihood of interaction can be defined by qualitative considerations on a fuzzy scale of 0 to 1. The fuzzy scale used in the case is depicted in **Table 9** (Qureshi et al., 2008).

Table 9. Fuzzy reachability scale.

Possibility of reachability	**Nil**	**Very low**	**Low**	**Medium**	**High**	**Very high**	**Full**
Value on the scale	0	0.1	0.3	0.5	0.7	0.9	1.0

4.8 Development of Fuzzy Direct Relationship Matrix (FDRM)

By analysing the direct relationships among the barriers in **Table 3**, a resultant direct reachability matrix (DRM) was derived. Here, transitivity was disregarded and the diagonal entries set to 0. The numerical value of reachability is integrated into DRM to produce a fuzzy direct relationship matrix (FDRM). **Tables 10** and **11** present the BDRM and FDRM relevant to the current case study.

Table 10. BDRM.

Barrier No.	**Barrier name**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1.	No research motivation post-promotion	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2.	Lack of professional development	1	0	1	0	0	0	0	0	0	1	0	0	0	0	0
3.	Weak research and language skills	1	0	0	0	0	0	0	0	0	1	0	1	1	0	0
4.	Heavy family commitments	1	1	0	0	0	0	0	0	0	0	0	1	1	0	0

Table 10 continued…

5.	No research incentives and rewards	1	1	0	0	0	0	0	0	0	1	0	0	0	1	0
6.	Lack of resources	1	1	1	0	0	0	0	0	0	0	0	1	1	1	1
7.	Teaching and service workload	1	1	0	0	0	0	0	0	0	0	0	1	1	0	0
8.	Tight research grant criteria	1	0	0	0	0	1	0	0	0	0	0	0	0	1	0
9.	No industry support	1	0	0	0	0	1	0	0	0	0	0	0	1	0	1
10.	Absence of recognition	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0
11.	Low stakeholder relevance of research	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0
12.	Top-journal rejection phobia	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13.	No intrinsic research motivation	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
14.	Weak research culture	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1
15.	Weak collaboration and networking	1	1	1	0	0	0	0	0	1	1	0	1	1	0	0

4.9 Fuzzy Indirect Relationship Analysis

The next step is to derive indirect relationships among barriers from FDRM. The matrix was multiplied several times until the enablers' driving and dependence powers were determined. Fuzzy matrix multiplication is a generalised version of the Boolean matrix multiplication, which forms the basis of the augmentation process. Following the rule from fuzzy set theory, the product of two fuzzy matrices is also a fuzzy matrix: Fuzzy set C is the result of multiplying fuzzy sets A and B in the equation below.

$$C = A \times B = max\ k\ [min\ (a_{ik}, b_{kj})] \tag{1}$$

where, A = (a_{ik}) and B = (b_{kj}) are two fuzzy metrics.

Table 11. FDRM.

Barrier No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Sum
1.	0	0	0	0.3	0.7	0	0	0	0	0	0	0	0	0	0	1
2.	0	0	0	0	0.5	0	0	0	0	0	0	0	0	0	0	0.5
3.	0.3	0	0	0.7	0.7	0	0	0	0	0	0	0	0	0	0	1.7
4.	0	0	0	0	0.3	0.3	0	0	0.7	0	0.3	0	0	0	0	1.6
5.	0	0	0	0	0	0.7	0	0.5	0.7	0	0.7	0	0	0	0.5	3.1
6.	0	0	0	0	0	0	0	0.5	0	0	0	0.7	0.3	0	0.7	2.2
7.	0	0	0	0	0	0	0	0	0	0.9	0	0	0	0	0	0.9
8.	0	0	0	0	0	0	0.5	0	0	0.7	0	0	0	0.9	0	2.1
9.	0	0	0	0	0	0.1	0.3	0	0	0	0	0	0.7	0	0	1.1
10.	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11.	0	0	0	0	0	0.5	0.5	0.5	0	0.3	0	0.7	0	0.3	0.5	3.3
12.	0	0	0	0	0	0	0.5	0.9	0	0.3	0	0	0.5	0.3	0.7	3.2
13.	0	0	0	0	0	0	0.7	0.5	0	0.7	0	0.5	0	0	0.7	3.1
14.	0	0	0	0	0	0	0	0	0	0.9	0	0	0	0	0	0.9
15.	0	0	0	0	0	0	0.7	0.5	0	0.7	0	0.7	0.3	0.5	0	3.4
Sum	0.3	0	0	1	2.2	1.6	3.2	3.4	1.4	4.5	1	2.6	1.8	2	3.1	

4.10 Fuzzy Matrix Stabilization

The fuzzy matrix reached stability at the eighth stage. The driving and reliance powers of individual barriers were calculated by adding the interaction possibilities in their respective rows and columns (**Table 12**). The ranks of the driving power of a barrier decided the hierarchy of that barrier in the system.

Table 12. Fuzzy stabilised matrix.

Barrier No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Sum
1.	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2.	0.3	0	0	0	0	0	0	0	0	0.3	0	0.5	0.5	0	0	1.6
3.	0.5	0	0.5	0	0	0	0	0	0	0.3	0	0	0	0	0	1.3

Table 12 continued…

4.	0.3	0	0.3	0	0	0	0	0	0	0.3	0	0	0	0	0	0.9
5.	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0	0.5	0.5	0	0.5	0.5	0.5	0.5	6.5
6.	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0	0.5	0.9	0	0.5	0.5	0.5	0.5	6.9
7.	0.5	0	0.5	0	0	0	0	0	0	0.5	0	0	0	0	0	1.5
8.	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0	0.5	0.5	0	0.5	0.5	0.5	0.5	6.5
9.	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0	0.5	0.5	0	0.5	0.5	0.5	0.5	6.5
10.	0	0	0	0	0	0	0	0	0	0.9	0	0	0	0	0	0.9
11.	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12.	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13.	0.3	0	0	0	0	0	0	0	0	0.3	0	0.5	0.5	0	0	1.6
14.	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0	0.5	0.7	0	0.5	0.5	0.5	0.5	6.7
15.	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0	0.5	0.5	0	0.5	0.5	0.5	0.5	6.5
Sum	4.9	3	4.3	3	3	3	3	0	3	6.2	0	4	4	3	3	

4.11 Fuzzy MICMAC Analysis

Similar to MICMAC, the 15 barriers were grouped under 4 categories by applying Fuzzy MICMAC (**Figure 2**). Barriers in Cluster I are autonomous, quite disconnected from the other barriers in the system due to their weak dependence power and low driving power. The dependent barriers in Cluster II possess high dependence power and a poor driving power. Linkage barriers with high driving as well as dependence power are placed in Cluster III. These are susceptible to changes in the driving barriers. The independent barriers in Cluster IV are shown to have a strong driving power and minimal reliance on other barriers.

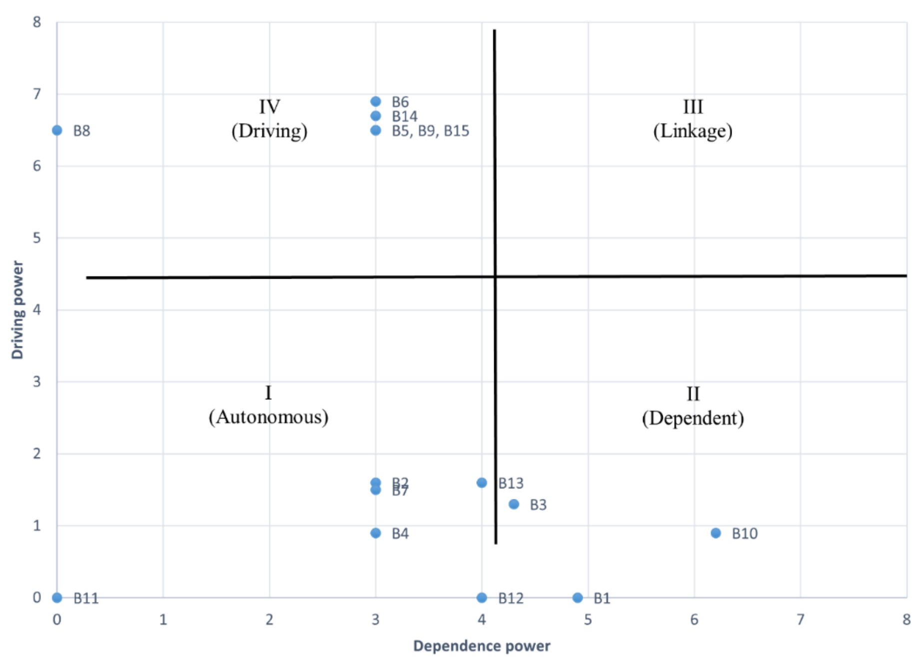

Figure 2. FMICMAC classification of barriers.

4.12 Robustness and Sensitivity Analysis

Given the reliance on expert judgments and fuzzy linguistic scales, robustness checks were undertaken to assess the stability of the derived hierarchy and fuzzy MICMAC classifications. First, majority-rule validation was applied during barrier selection and relationship identification to reduce the influence of outlier judgments. Second, a limited sensitivity check was conducted by marginally varying selected fuzzy scale values (±1 level on the triangular fuzzy number scale) for key barrier relationships and re-examining driving and dependence powers.

The analysis indicated no substantive change in the hierarchical positioning of dominant driving barriers or in fuzzy MICMAC quadrant membership. This suggests that the structural results are stable to slight variations in expert judgment. Such perturbation-based sensitivity checks are commonly recommended in fuzzy MCDM research to assess robustness without extensive resampling procedures (Govindan & Jepsen, 2016; Büyüközkan & Göçer, 2018).

5. Results and Discussion

The TISM hierarchy positions institutional capability and support-related constraints at the foundational levels based on expert-perceived causal precedence, because these barriers enable or restrict the availability of resources, autonomy, and collaboration channels that research activity depends on. For example, limited research funding and restrictive grant norms suppress faculty engagement in externally funded projects and hinder the development of collaborative and industry-aligned research agendas as perceived by the participating experts. Similarly, a weak research culture and the absence of incentives reduce the perceived value and reward of engaging in scholarly work. Within the interpretive logic of TISM, these barriers shape how effectively the system functions. As a result, these appear as major drivers across both the TISM and Fuzzy MICMAC models in terms of perceived structural influence.

This finding aligns with prior research that emphasises the role of institutional resources, governance, and research-supportive environments in shaping academic productivity, particularly in higher education systems under performance pressure (Teodorescu, 2000; Bland et al., 2005; Hazelkorn, 2015).

Notably, common barriers such as teaching workload, research motivation, and psychological pressures (e.g., rejection anxiety) do not drive the system but instead are positioned as downstream constraints in the expert-derived hierarchy. This appears to diverge from prior literature that positions workload and motivation as dominant factors in low research productivity (Hesli & Lee, 2011; Ramírez-Montoya et al., 2023; Orfan et al., 2024; Wang et al., 2024). This difference reflects variation in analytical perspective rather than a contradiction of empirical evidence. While prior studies typically examine direct individual-level associations, the present study captures expert perceptions of systemic ordering among barriers within Indian management academia. The results reveal that these constraints become consequential, particularly when institutions fail to supply the requisite research environment and support mechanisms. The insight offers an interesting perspective by shifting the focus from individual shortcomings to systemic enablers of academic performance as understood by domain experts.

Similar system-level interpretations have been advanced in studies that argue individual motivation and effort are contingent on organisational context, incentive alignment, and institutional culture rather than operating independently (Jung, 2014; Brew et al., 2016).

Another surprising relationship is that professional development, often emphasised as essential in faculty improvement frameworks, emerges as an autonomous barrier with minimal systemic influence. This suggests that training alone may be insufficient to resolve productivity constraints unless it is coupled with access to resources and collaborative mentoring opportunities. Similarly, low stakeholder relevance of research does not affect other barriers much. This indicates that management research quality may trace back more strongly to underlying institutional and incentive structures.

This observation echoes prior work suggesting that professional development initiatives yield limited returns when implemented in isolation from broader organisational and resource reforms (Smolentseva, 2011; Gonzalez et al., 2019).

Furthermore, the absence of linkage variables in the Fuzzy MICMAC output indicates that feedback loops are currently weak and that the system functions in a stable but top-down hierarchical manner according to the fuzzy dependence–driving classification. This means that progress is unlikely without deliberate action at the foundational level from the perspective of the modelled system.

Table 13. Solution strategies based on FMICMAC categorisation of barriers.

Quadrant / Barrier type	**Key barriers (code & description)**	**Strategic focus**	**Recommended managerial / Policy actions**
Driving (High Driving, Low Dependence)	B5 – No research incentives and rewards B6 – Lack of resources B8 – Tight research grant criteria B9 – No industry support B14 – Weak research culture B15 – Weak collaboration and networking	Systemic lift and institutional reform	• Simplify research-grant procedures and decentralise fund allocation. • Ensure steady financial, infrastructural, and digital research support. • Like the UK and Australia, set up performance- based research funds with internal seed funding. • Establish long-term industry-academia ties in the form of research consortia. • Foster mentorship from senior/experienced groups, and collaboration interest among peers across institutions.
Dependent (Low Driving, High Dependence)	B1 – No research motivation post-promotion B3 – Weak research and language skills B10 – Absence of recognition B12 – Top-journal rejection phobia	Motivation and recognition platforms	• Revise promotion policies to align with management research quality and impact. • Offer regular skill-development workshops on research, writing and publishing. • Recognise and reward impactful research in performance appraisals. • Formal mentoring for intellectual guidance and editorial assistance to reduce publication anxiety.
Autonomous (Low Driving, Low Dependence)	B2 – Lack of professional development B4 – Heavy family commitments B7 – Teaching and service workload B11 – Low stakeholder relevance of research B13 – No intrinsic research motivation	Faculty engagement and workload optimization	• Create teaching, research, and service balance through workload flexibility. • Design strategic professional development and career-planning programs linked to research outcomes. • Encourage practice-based and stakeholder-relevant management research themes. • Offer counselling and wellness support to mitigate personal and professional stress.
Linkage (High Driving, High Dependence)	(None identified)	Not applicable	The absence of linkage variables indicates a stable and well-stratified structure with minimal feedback instability. However, regular monitoring is recommended to prevent the emergence of new interdependent barriers as policies evolve.

Note: *Given resource constraints, interventions targeting driving barriers are expected to yield the highest system-wide impact and should be prioritised before addressing dependent or autonomous barriers.*

Comparable hierarchical patterns have been reported in other ISM- and MICMAC-based studies of higher education systems, where institutional drivers dominate, and individual-level constraints emerge as secondary effects (Talib & Rahman, 2020; Ocampo et al., 2022). The alignment between TISM and Fuzzy MICMAC reinforces the internal robustness of the model, indicating that interventions that prioritise funding, administrative flexibility, mentoring, networking, and a strong research culture are perceived by experts as having the most transformational potential. Addressing individual-level barriers without strengthening these foundations risks short-term fixes that do not alter long-run research trajectories within the current institutional configuration.

Taken together, the findings complement rather than contradict the extant literature by reframing commonly studied individual barriers within a broader institutional and systemic perspective. **Table 13** offers potential strategies and solutions at managerial as well as policy levels.

6. Implications

The findings indicate that enhancing research productivity in management academia necessitates systemic reforms rather than solely targeting individual faculty interventions. Easing access to research funding, streamlining internal research approval processes, and incorporating incentives for publication and collaboration can drive improvements across various institutional levels. Establishing a supportive research culture via mentoring frameworks, collaborative networks, and recognition systems is crucial for early-career academics. Policymakers and accreditation agencies can enhance these initiatives by investing in both digital and physical research infrastructure, as well as by aligning resource allocation criteria with measurable research engagement.

Along with this, B-schools should provide an environment that encourages collaboration and support to help academic research. B-schools and management institutions ought to establish mentoring programs, research clusters, and multidisciplinary platforms that link novice faculty with seasoned scholars and industry experts. These kinds of projects may tie scattered individual efforts into an active, networked research community.

Collectively, the strategy implications offer a targeted reform agenda that allows academics to flourish in a setting that structurally encourages research rather than depending solely on the self-motivation of academicians. The insights from this study provide actionable starting points for administrators, politicians, and accreditation entities aiming to cultivate a robust and enduring research culture within Indian management academia.

Given the hierarchical structure revealed by the TISM and fuzzy MICMAC analyses, not all interventions carry equal urgency. Barriers classified as driving variables represent foundational constraints that shape multiple downstream outcomes. Under conditions of limited resources, policy and managerial attention should therefore prioritise interventions targeting these driving barriers, as improvements at this level are more likely to generate cascading benefits across the system. In contrast, initiatives aimed at dependent and autonomous barriers may be more effective once enabling institutional conditions are strengthened.

6.1 Limitations

This study has several limitations that should be considered when interpreting the findings. First, the TISM–Fuzzy MICMAC approach captures expert-perceived structural relationships among barriers rather than empirically tested causal effects. While this provides valuable insight into perceived system dynamics, alternative explanations such as reverse causality cannot be ruled out.

Second, the findings are context-specific to Indian management academia and reflect discipline-specific conditions, including teaching-intensive workloads and applied research expectations. Caution is therefore required when transferring the hierarchy or policy implications to other disciplinary or national contexts.

Third, although expert diversity and consensus thresholds were used to mitigate bias, the results remain dependent on expert judgment and the fuzzy scaling assumptions employed. Future studies may complement this approach with longitudinal or quantitative designs to empirically test the strength and direction of relationships identified here.

7. Conclusion

The present study offers actionable insights for management leaders of Indian higher education. Institutions must establish clear and effective incentive systems fostering engagement of academicians with research and professional development. Additionally, a research culture that emphasises mentoring, collaboration, and recognition must be developed to enhance the quality and consistency of outputs. Support policies must be formulated and ensured to reach the bottom-most level, individual faculty members, rather than catering to surface-level departmental needs. Furthermore, research ought to be directed towards the challenges faced by Indian businesses, thereby shifting the focus to management faculty in the Indian context. In this regard, for academic research to provide practical solutions, research collaborations with the industry are imperative. Future research on management research productivity may investigate the average-ranked management institutes in India to identify barriers to research productivity across various fields or geographical regions. thereby assessing the applicability of these recommendations and areas requiring refinement.

Conflicts of Interest

The authors confirm that there is no conflict of interest to declare for this publication.

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Appendix A

Each respondent holds diverse experiences across varied management and industry sectors and is a recognized expert in their teaching/research/industry domains. **Table A** provides detailed demographic information of the respondents, including their institution ownership and NIRF rank range.

Table A. Individual respondent profile**.**

Respondent	Research orientation	Institution ownership	NIRF rank	Gender	Career length
ID01	Research active	Private	1-25	Female	6 years
ID02	Not research active	Private	1-25	Female	7 years
ID03	Research active	Private	51-75	Female	10 years or more
ID04	Research active	Private	51-75	Female	10 years or more
ID05	Research active	Private	26-50	Male	10 years or more
ID06	Research active	Private	26-50	Female	Less than 10 years
ID07	Research active	Private	26-50	Female	Less than 10 years
ID08	Not research active	Private	Industry	Male	Less than 10 years
ID09	Research active	Public	76-100	Male	Less than 10 years
ID10	Research active	Public	1-25	Male	10 years or more
ID11	Research active	Public	51-75	Male	10 years or more
ID12	Research active	Public	76-100	Female	Less than 10 years
ID13	Not research active	Private	76-100	Male	10 years or more
ID14	Research active	Private	Industry	Female	10 years or more

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